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Weed Detection for Precision Agriculture: A Comprehensive Review

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Abstract: *Growing crops and rearing animals to produce food, clothes, and other everyday necessities is known as agriculture. Unwanted plants that grow where they are not needed typically in gardens, among crops, or on farmland are called weeds. They can lower crop yields and make farming more difficult by competing with crops and other plants for resources like water, nutrients, sunlight, and space. Precision agriculture is a clever agricultural method that helps farmers grow crops more effectively by utilizing contemporary equipment and technology. It all comes down to treating each section of the field with the appropriate quantity of water, fertilizer, or care rather than treating the entire field in the same way. For both efficient weed control and sustainable wheat production, accurate weed detection is essential. Weed detection is a critical task in precision agriculture, enabling targeted intervention and reducing herbicide use. Convolutional Neural Networks (CNNs), a type of deep learning algorithm, have demonstrated significant potential in automating this procedure. Recent studies on the use of deep learning methods for weed identification in different crops are reviewed in this publication. We analyze commonly used CNN architectures, including YOLO, R-CNN, and others, along with image acquisition methods, datasets, and performance metrics. The review highlights the advancements, challenges, and future directions in deep learning-based weed detection, providing valuable insights for researchers and practitioners in the field of precision agriculture.*

Keywords: Agriculture, Convolutional neural networks (CNNs), Crops, Deep learning, Image processing, Weeds

I. INTRODUCTION

The growing global population has led to a greater demand for production, making sustainable agricultural management practices increasingly important. Weeds are a major issue in agriculture because they compete with crops for sunlight, water, and nutrients [1]. Their presence significantly reduces yield and drives up production costs. Therefore, a key component of increasing production and guaranteeing sustainable agricultural practices is effective weed management. Hand labor or the careless uses of herbicides are the traditional methods of controlling weeds, and they can be costly, ineffective, and detrimental to the environment [5]. Technological developments in machine learning and computer vision provide a revolutionary answer to this problem. Deep learning-based image processing methods in particular have shown great promise for automating weed detection and other agricultural activities [2]. Weed management is a critical aspect of agricultural production, directly impacting crop yields and overall farm profitability. Traditional methods, relying heavily on manual labor and indiscriminate herbicide application, present significant challenges in terms of efficiency, cost-effectiveness, and environmental sustainability [8]. Precision agriculture, which aims to optimize resource use through advanced technologies, offers a pathway to more targeted and sustainable weed control [4]. Deep learning, a subfield of artificial intelligence, has emerged as a transformative technology in computer vision, enabling automated image analysis with unprecedented accuracy [10]. Its application to weed detection holds immense potential for revolutionizing agricultural practices. This review paper synthesizes recent research on the use of deep learning algorithms for weed detection in precision agriculture. It looks at important developments in model architectures, data collection, and performance assessment, stressing both the successes and the obstacles now facing

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the field. This paper attempts to guide future research and aid in the creation of efficient, deep learning-based weed management solutions by offering a thorough summary of the state of the art.

II. LITERATURE SURVEY

Islam et al. [1] evaluated the efficacy of several machine learning techniques, such as random forest (RF), support vector machine (SVM), and k-nearest neighbors (KNN), in weed detection using UAV images from an Australian chilli crop field. Performance was compared using the following evaluation criteria: accuracy, precision, recall, false positive rate, and kappa coefficient. The machine learning algorithms are simulated using MATLAB, and the obtained weed detection accuracies are 63% with KNN, 96% with RF, and 94% with SVM. According to this study, RF and SVM algorithms are effective, useful, and simple to apply for weed detection in UAV photos. The study focuses on UAV photos taken in a particular crop area in Australia. This restricts the findings' applicability to other crop varieties, geographical areas, and environmental circumstances. Only three machine learning algorithms—RF, SVM, and KNN—are evaluated in this work. Deep learning-based techniques, such as convolutional neural networks, are examples of more modern or sophisticated algorithms that are not taken into account yet could produce better outcomes, particularly for image-based jobs.

A unique method that combines deep learning and image processing technologies is offered by Jin et al. [2]. Initially, a trained CenterNet model was used to identify vegetables and enclose them with bounding boxes. After that, the remaining green objects that slipped out of the boundary boxes were considered weeds. By focusing solely on crop identification, the model avoids dealing with various weed species. Furthermore, this technique can greatly reduce the amount of the training image dataset and the complexity of weed detection, enhancing weed identification performance and accuracy. To exclude weeds from the background, a color index-based segmentation technique was used in image processing.

The employed color index based on Bayesian classification error was computed and evaluated using Genetic Algorithms (GAs). During the field test, the trained CenterNet model achieved an F1 score of 0.953, a precision of 95.6%, and a recall of 95.0%. The proposed index $-19R + 24G - 2B \geq 862$ yields exceptional segmentation quality at a substantially lower processing cost than the popular ExG index. The experiment's results demonstrate the viability of the recommended method for ground-based weed identification in vegetable plantations. The method's applicability to other crop kinds with distinct traits may be limited because it is specifically designed for vegetable plantations. In complex situations, such as fields with different soil backgrounds, shadows, or non-green weeds, relying primarily on a single color index may not work well.

By comparing various YOLO versions within two well-known deep learning frameworks, Syed Ijaz Ul Haq et al. [3] explore real-time weed identification in wheat crops using deep learning. The approach of the study focuses on obtaining a sizable dataset of 6000 RGB photos that were gathered from commercial wheat fields and the research farm of PMAS Arid Agriculture University.This dataset was captured using a combination of a Samsung A31s mobile camera and a Logitech C920 Pro HD webcam, ensuring a degree of variability in image acquisition. Crucially, images were acquired under diverse weather conditions and from varying heights and angles, aiming to enhance the robustness of the resulting models. The research explored YOLOv3-Tiny, YOLOv4-Tiny, and multiple versions of YOLOv5, implemented using both TensorFlow and PyTorch. All models were trained on an NVIDIA RTX 2070 GPU, with careful hyperparameter tuning to optimize performance. According to the study, the PyTorch framework continuously beat TensorFlow in terms of prediction accuracy and execution time. With inference times of 9.43 ms and 12.38 ms, respectively, YOLOv5l and YOLOv5m within the PyTorch framework showed the maximum efficacy, reaching weed removal accuracy of 0.89 and 0.91. The restricted investigation of the models' performance across a wider variety of weed species and growth stages is one possible weakness in this study, which may affect its applicability in various agricultural contexts.Further, there is limited discussion of the performance of the models under extreme lighting conditions.

Guzel et al. [4] investigated the effectiveness of various YOLOv5 models for weed detection in wheat fields.The most accurate model was found to be YOLOv5s, which showed excellent accuracy across a range of weed species and growth phases. The YOLOv5s model offered a reasonable mix between accuracy and computing efficiency, even if larger models like YOLOv5m, YOLOv5l, and YOLOv5x had slightly higher accuracy. The study also showed how the generated dataset may be used as a benchmark for future research on weed detection, enabling comparisons between different deep learning models and approaches. Future studies will look at more recent versions of YOLO, evaluate performance using 3D data, and use state-of-the-art sensor technologies to further increase the precision and effectiveness of weed detection.

A unique three-channel weed recognition technique that makes use of multi-modal information from RGB and depth images was presented by Xu et al. [5]. We improved the appropriateness of depth images for CNN-based feature learning by recoding them into Phase-Histogram (PHA) images. Techniques successfully integrate the complementing data from both modalities, leading to increased accuracy in weed identification. With a noteworthy IoU of 89.3%, the suggested three-channel network—which is intended for feature- and decision-level fusion—proved its capacity to precisely identify a range of weed species in wheat fields. Even while deep learning has made great strides in weed detection, there are still a number of obstacles to overcome. It's possible that datasets used to train models aren't varied enough to represent unpredictability in the real world. Dependence on powerful hardware may restrict useful applications.

Sarmad Hameed et al. [6] presents a multi-stage image processing methodology for detecting weeds, wheat, and barren land in wheat fields using UAV-acquired RGB images. The study proposes a three-phase approach tailored to different crop growth stages: barren land detection using edge detection (Phase 1), differentiation of green wheat and weeds using HSV color space analysis (Phase 2), and differentiation of yellowing wheat and green weeds using background subtraction (Phase 3). Aerial images of a 5-acre wheat field were captured using a Phantom 4 UAV at three growth stages and processed in MATLAB. The results are presented visually and quantitatively, detailing the percentage of image area occupied by weeds and wheat in sample images. Although the paper presents a useful strategy, it has certain shortcomings, including limited generalization to other crops or environments, no robustness analysis to changes in noise and lighting, no comparison with the most advanced deep learning techniques, and limited quantitative accuracy metrics like precision, recall, and F1-score.

In their deep learning-based method for classifying weed plants, Sheeraz Arif et al. [9] introduce a hybrid architecture that combines the advantages of long short-term memory (LSTM) networks and convolutional neural networks (CNNs). The technique focuses on using CNNs to directly extract reliable and discriminative features from input photos of different types of weed plants. An LSTM network is subsequently fed these extracted features, which identify patterns and spatial hierarchies in the images, one after the other. The LSTM component is designed to model temporal dependencies within the feature sequence, allowing the network to better understand the relationships between different parts of the plant and thus optimize the classification process. The authors use a variety of data augmentation techniques, such as zooming, rotating, color changes, flipping, shifting, brightness adjustments, and cropping, to increase the training dataset and improve the model's generalization capacity and reduce overfitting. The performance of the proposed CNN-LSTM architecture is rigorously evaluated using 5-fold cross-validation, providing a robust estimate of its classification accuracy. The results demonstrate that the CNN-LSTM method achieves a high average classification accuracy of 99.36%, surpassing the performance of other established deep learning models such as Inception-v3 and ResNet-50. A potential gap in this research is the limited detailed information about the specific diversity of the nine weed species included in the dataset and the precise field conditions (e.g., lighting, soil type, growth stage) under which the images were captured, which could influence the model's performance in broader agricultural settings.

Md. Najmul Mowla et al. [10] introduces CovWNET, a novel and computationally efficient convolutional neural network (CNN) architecture designed for weed detection. Five 2D convolutional layers and three fully linked layers make up the simplified design of the suggested CovWNET architecture. To improve feature extraction and reduce overfitting, each convolutional layer uses 3x3 kernels and includes max pooling and dropout layers. Throughout the network, ReLU activation functions are utilized, and for the final classification, a SoftMax function is implemented. CovWNET's performance is thoroughly assessed in the study by contrasting it with a number of reputable transfer learning models, such as DenseNet201, MobileNetV2, VGG16, VGG19, and Xception. The V2 Plant Seedlings Dataset, which comprises 5,539 photos of 12 distinct plant species, is used for the evaluation. To ensure robust training,

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the dataset undergoes preprocessing and data augmentation, and models are trained from scratch using the Adam optimizer within the TensorFlow Keras framework, leveraging the computational resources of Google Collaboratory with a Tesla T4 GPU. CovWNET achieves a competitive accuracy of 91.33% on the test set, demonstrating a favorable trade-off between performance and model complexity, as it exhibits a smaller size (fewer parameters) compared to several benchmark models. A potential gap in this research is the limited exploration of CovWNET's performance under more challenging real-world scenarios, such as varying illumination conditions, complex background clutter, and a greater diversity of weed species, which could further validate its practical applicability in agricultural settings.

Sneha N Sneha et al. [11] presents a comparative analysis of three prominent object recognition algorithms for the task of weed identification in agricultural settings: YOLOv3, R-CNN, and CenterNet. The study's methodology encompasses the creation of a dataset comprising 1125 weed images, followed by essential preprocessing steps, including image resizing and normalization. This dataset was subsequently partitioned into training (750 images) and testing (375 images) subsets. The training phase involved leveraging pre-trained models, specifically ResNet, VGG, and Inception, as backbone architectures, which were then fine-tuned to adapt to the specific characteristics of the weed identification task. In addition to algorithm comparison, the paper introduces a method for estimating weed size by measuring the length and width of detected weed regions, employing image processing techniques such as edge detection and grayscale image analysis. Furthermore, the study outlines a procedure for predicting weed growth based on CNN-derived height and width measurements. The paper reports the following average accuracies for the compared algorithms: YOLOv3 (98%), R-CNN (93%), and CenterNet (86%). While YOLOv3 demonstrates the highest overall accuracy, the authors note that R-CNN exhibits superior performance in image processing and classification tasks. A potential gap in this research is the limited exploration of the models' performance on more diverse datasets, encompassing a wider range of field conditions, weed species, and growth stages, which could provide a more comprehensive assessment of their robustness and generalizability in real-world agricultural applications.

Furthermore, more research is required to assess how well models work in actual field settings, such as changing weather and lighting. The cost and accessibility of depth sensors, as well as their susceptibility to external influences, may be obstacles for multi-modal techniques. Moreover, these techniques can be highly computationally complex. Last but not least, deep learning models are susceptible to hostile attacks and frequently have un-interpretable decision-making processes. Developing strong, effective, and dependable weed detection systems that can be incorporated into agricultural operations requires addressing these issues.

III. METHODOLOGY USED

Weeds, often known as unwanted plants, are a major problem in agricultural environments. These plants immediately compete with crops for resources like sunlight, water, necessary nutrients, and physical space, growing in regions that are not intended for them. The development and production of the intended crop are always hampered by this fierce competition, which frequently leads to notable drops in harvest quantity and quality.

Beyond resource competition, weeds can serve as hosts for various insect pests and plant diseases, contributing to their proliferation and posing a direct threat to crop health. Their physical presence can also complicate routine farm activities, making planting, cultivation, and harvesting more labor-intensive and expensive. Moreover, certain weed species are known to release biochemicals that can suppress crop germination or growth (allelopathy), or they may contaminate harvested produce, thereby diminishing its commercial value.

Historically, weed control has largely depended on manual labor and the broad application of synthetic herbicides. While these conventional approaches have offered some degree of effectiveness, they come with considerable drawbacks. Manual removal is often cost-prohibitive and impractical for large-scale farming, while the widespread use of herbicides raises significant environmental concerns, including soil and water contamination, a reduction in biodiversity, and the accelerating evolution of herbicide-resistant weed populations. These inherent limitations highlight the urgent necessity for the development and adoption of more precise, efficient, and ecologically sound weed management strategies in contemporary agriculture. Consequently, accurate weed detection and targeted control are fundamental to safeguarding food production, optimizing agricultural inputs, and fostering sustainable farming systems.

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Fig.1 Sample pictures of weeds

Research articles that concentrate on the application of deep learning for weed detection in agricultural fields are methodically examined in this review. A comprehensive literature search was conducted using databases such as IEEE Xplore, ScienceDirect, Springer, and Google Scholar, with keywords including "weed detection", "deep learning", "CNN", "YOLO", and "precision agriculture". Studies were selected based on their relevance, use of deep learning methods, and experimental validation in real or simulated agricultural environments. The selected papers were reviewed and categorized based on model architectures (e.g., YOLO, R-CNN, CNN-LSTM), datasets used, image acquisition techniques (UAVs, RGB, depth cameras), performance metrics (accuracy, F1-score, IoU), and practical limitations. A comparative analysis was performed to highlight current trends, research gaps, and technological advancements in this domain.

The methodological analysis focuses on four main aspects: (1) image acquisition techniques, (2) deep learning model architectures, (3) datasets used for training and evaluation, and (4) performance metrics and evaluation methods.

1. Image Acquisition Techniques: Most of the studies reviewed employed RGB images as the primary input format, captured using various devices such as UAVs (Unmanned Aerial Vehicles), mobile cameras, and webcams. For instance, Syed Ijaz Ul Haq et al. [3] used a Samsung A31s and Logitech C920 Pro HD webcam under varying environmental conditions, while Sarmad Hameed et al. [6] utilized UAVs to capture images at different crop growth stages. Some studies, such as Xu et al. [5], extended image modalities to include depth data, processed into phase-histogram images to enhance spatial feature learning.

2. Deep Learning Model Architectures: A variety of Convolutional Neural Network (CNN)- based models were used in the studies:

YOLO Variants (YOLOv3, YOLOv4, YOLOv5): Frequently used for real-time weed detection due to their fast inference and high accuracy. Guzel et al. [4] and Ijaz Ul Haq et al. [3] found YOLOv5l and YOLOv5m to perform best in terms of accuracy and speed.

R-CNN and CenterNet: Used for object detection tasks. Sneha N. et al. [11] reported that YOLOv3 outperformed R-CNN and CenterNet in overall accuracy.

Custom CNN Architectures: Md. Najmul Mowla et al. [10] proposed CovWNET, a lightweight CNN model optimized for weed detection.

Hybrid Architectures (CNN + LSTM): Sheeraz Arif et al. [9] integrated CNNs with LSTM layers to leverage temporal relationships within image features, significantly boosting classification accuracy.

These architectures were implemented using popular frameworks like TensorFlow and PyTorch. Comparative evaluations often showed PyTorch-based models to be more efficient in execution time and accuracy.

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3. Datasets: The reviewed studies utilized both publicly available and custom-collected datasets. Examples include:

V2 Plant Seedlings Dataset [10]: Contains images of 12 plant species and was used for benchmarking CNN performance.

Custom Datasets: Multiple studies captured and annotated weed images specific to wheat fields and local conditions (e.g., PMAS Arid Agriculture University dataset [3], UAV images of Australian chilli crops [1]).

Image Augmentation: Techniques such as zooming, rotation, flipping, brightness adjustment, and cropping were commonly applied to enhance model generalization and prevent overfitting.

4. Performance Metrics and Evaluation: To assess the models' effectiveness, researchers adopted metrics such as:

Accuracy, Precision, Recall, and F1-Score: Standard metrics for evaluating classification and detection tasks.

Intersection over Union (IoU): Used for object detection precision, particularly in bounding box-based models.

Inference Time and Model Size: Considered for evaluating real-time usability and computational efficiency.

For example, Jin et al. [2] reported a precision of 95.6% and an F1-score of 0.953 using CenterNet with color index segmentation, while CovWNET achieved 91.33% accuracy with reduced model complexity [10].

Here is a **comparison table** that provides context for each study, including the model/technique used, the nature and size of the dataset, performance metrics, and key observations:

Author(s)	Model / Technique	Dataset Details	Performance Metrics	Key Observations
Islam et al. [1]	Random Forest (RF), SVM, KNN	UAV images from Australian chilli fields	RF: 96%, SVM: 94%, KNN: 63%	RF and SVM were more accurate; limited crop diversity and model types.
Jin et al. [2]	CenterNet + Color Index Segmentation	Custom vegetable crop dataset; uses bounding boxes and color thresholds	F1-score: 0.953, Precision: 95.6%	Avoids weed classification; fast and lightweight; limited to green vegetation.
Ijaz Ul Haq et al. [3]	YOLOv3-Tiny, YOLOv4-Tiny, YOLOv5 (PyTorch & TensorFlow)	6000 images (RGB) from wheat fields using smartphones and webcams	YOLOv5m: Accuracy 91%, Inference 12.38 ms	PyTorch outperforms TensorFlow; good real-time detection with YOLOv5.
Guzel et al. [4]	YOLOv5s, YOLOv5m/l/x	Wheat crop dataset with varied weed types and growth stages	YOLOv5s: High accuracy, low latency	Balanced speed and accuracy; suggested as baseline for future weed detection work.
Xu et al. [5]	CNN (RGB + Depth → Phase Histogram)	RGB & Depth images of wheat fields	IoU: 89.3%	Multi-modal fusion boosts accuracy; PHA encoding improves depth image usability.
Hameed et al. [6]	Multi-stage image processing (Edge, HSV, Background Subtraction)	UAV RGB images at 3 wheat growth stages	Visual quantification only	Lightweight; lacks deep learning comparison; effective for field-level area mapping.
Arif et al. [9]	CNN-LSTM Hybrid	Images of 9 weed species; augmented with various transformations	Accuracy: 99.36% (5-fold CV)	Combines spatial (CNN) and sequential (LSTM) features; high generalization.
Mowla et al. [10]	CovWNET (custom CNN architecture)	V2 Plant Seedlings Dataset (5539 images, 12 species)	Accuracy: 91.33%	Efficient and lightweight; good trade-off between performance and model size.

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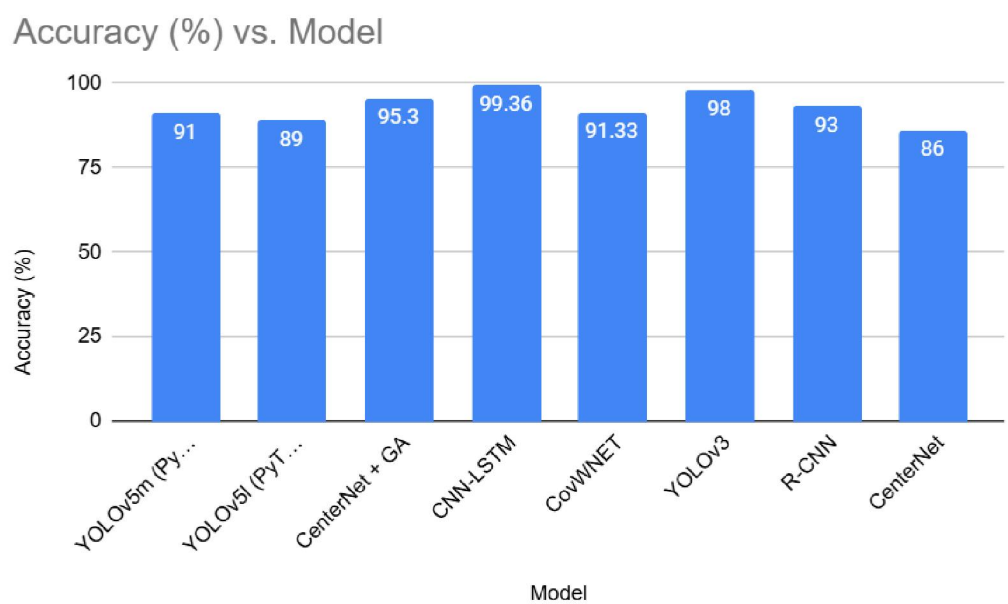
Author(s)	Model / Technique	Dataset Details	Performance Metrics	Key Observations
Sneha et al. [11]	YOLOv3, R-CNN, CenterNet + Measurement	1125 weed images; fine-tuned using ResNet, VGG, Inception	YOLOv3: 98%, R-CNN: 93%, CenterNet: 86%	YOLOv3 leads in detection; R-CNN better in classification; includes weed size prediction.



IV. CONCLUSION AND FUTURE WORK

This review paper has comprehensively analyzed recent developments in deep learning-based weed detection, with a focus on applications in precision agriculture. Through an evaluation of various models including YOLO, R-CNN, CNN-LSTM hybrids, and custom CNN architectures it is evident that deep learning has significantly enhanced the accuracy and efficiency of weed identification. These advancements support the transition toward automated, targeted weed management strategies, reducing herbicide use and improving crop yields. However, several challenges remain, particularly in adapting these models to real-world field conditions characterized by variable lighting, soil backgrounds, and diverse weed species. Additionally, the high computational requirements of many deep learning models present obstacles for real-time deployment in low-resource environments. This review offers critical insights into current techniques, performance benchmarks, and limitations, thereby providing a foundation for future innovations in sustainable agriculture.

Future research should aim to design lightweight, generalizable models that maintain high performance across diverse environmental conditions and crop types. There is a pressing need for larger, more diverse, and standardized datasets that better represent real-world agricultural scenarios. Incorporating multi-modal data sources, such as depth and thermal imagery alongside RGB data, may enhance model robustness and accuracy. Moreover, efforts should be directed toward optimizing models for deployment on edge computing devices, such as UAVs and field robots, to enable real-time weed detection. Research into explainable AI (XAI) for agricultural models will also be essential to foster transparency and trust among end-users. Lastly, improving model resilience to adversarial attacks and environmental noise will be vital for safe and reliable operation in practical field applications.

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